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The Core Literacy of College Counselors Based on Edge Intelligence and Lightweight Computing Under the Background of Information Technology and Students' Ideological and Political Education

Journal of Electrical Systems

***Abstract:* -** In recent times, there has been a lot of diseases arising day by day as a result of which people have become much concerned about their health. Thus it has become quite important to monitor the health. To address this, a real time health monitoring system has been proposed based on IoT. It has various sensors such as pulse oximeter, ECG, Temperature sensor. This device also has GSM module and it can send messages in case of emergency. This mobile health monitoring system can be used to check patient's health and the data can be stored on IOT cloud which can be fetched as and when required. This simple device monitors patient's health where big medical equipments cannot reach such as in rural areas and in this situation, this device serves as a boon. It is a compact device that can provide real time online information about patient's health conditions. The device stores the information about various health parameters which can be monitored by family members and doctor so that immediate action can be taken in case of an emergency.

Keywords: Internet of Things (IoT), Health Monitoring, Microcontroller ESP32, Real Time Monitoring, Arduino IoT Cloud, GSM Module

1. Introduction:

Core of socialist construction is ideological and political (IAP) education. As the primary hub for fostering the "Four Haves" in the interest of socialist development, colleges and institutions have a significant educational role to play. But the teaching of IAP theoretical courses lacks a uniform, scientific, methodical, and workable assessment index system. Therefore, it is imperative that current science and technology be used to build a comprehensive, impartial, and workable method for evaluating classroom instruction. Additionally, streamlining the evaluation process is a critical issue that requires immediate attention. As the cornerstone of socialist creation, funding IAP education programmes has always been a major priority for the party and the nation [1]. The ongoing overhaul of the market economic system is posing hitherto unheard-of difficulties for my nation's spiritual and cultural endeavours. At the Sixth Plenary Session of the Seventeenth Central Committee, which convened from October 15–18, 2011, a resolution was reached in this regard under the heading of "Deepening Reform of the Cultural System, Promoting the Development and Prosperity of Socialism Culture." Recognising the learning behaviours of students has been actively investigated utilising various wearable, embedded, and vision-based sensors [2]. The majority of researchers in vision-based behaviour recognition have mostly concentrated on video cameras because they may yield a wealth of data about surrounding environment. Conversely, wearable and embedded sensors in smartphones are compact, lightweight, and capable of resolving memory and computational problems. As such, they merit greater attention in the context of identifying student behaviour on cellphones [3]. When it comes to smartphone-based human behaviour detection, embedded sensor signals like those from gravity and accelerometers are frequently used to gather data. According to Marxist theory, thinking is a historical category that is influenced by the degree of scientific and technological advancement of the time as well as the practices and existence of people in a given era. Big data has resulted in significant conceptual and ideological emancipation, allowing individuals to develop new ways of speaking, thinking, managing, and innovating with big data. Big data thinking is essentially a new thought system that emerged in the big data era and is built upon big data technologies. The awareness that, when managed

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appropriately, public data can offer solutions to millions of people's pressing issues is known as "big data thinking." Big data thinking is an approach to problem-solving that makes use of data to study and uncover the law of development of things as well as to think, analyse, and solve problems using data and quantitative approaches. After the signals are gathered, ML algorithms are utilized to preprocess data to identify appropriate student behaviour and action. As a result, these systems are used in a wide range of practical applications in intelligent settings, including smart homes and healthcare systems. An intelligent human behaviour recognition system, for instance, utilized to continuously track a student's level of political as well as ideological education [4]. Students are driving force behind a nation's future growth, and their college years shape their perspective on life. The management of online courses for college students' ideological and political education (IPE) has become a crucial concern for online teaching instructors due to the ongoing advancements in network remote education. Modifications to instructional strategies may have an impact on students' acquisition of appropriate values and the quality of instruction. ML and DL technologies are used by many more sensor functions in smartphones to offer a technical path for comprehending state of students' online learning as well as raising bar for instructional management [5].

2. Research contribution:

To propose novel technique in students database security management and their idealogy analysis based on political education using mobile edge computing with lightweight security model

The students interest has been analysed using reinforcement convolutional adversarial radial neural networks. To proposed novel ideology model based political teaching quality enhancement with students interest based data analysis using artificial intelligence techniques.

The experimental results for various students interest in political education with security analysis using parameters like data integrity, throughput, training accuracy, mean precision, recall.

3. Related works:

Develop through education people who will be the defenders, architects, and heirs of socialism, upholding its core values. One of the most important parts of colleges' and universities' educational missions is offering IAP (ideology and politics) courses. The two components of the teaching process are instruction and learning. Assessing teachers' IPE is a far more difficult task than assessing the calibre of the output. Using fuzzy mathematics theory and methodology, [6] addressed each index grade offered by the assessment topic to obtain a comprehensive assessment of quality of instruction. During his research, Author [7] stated that when evaluating education blindly using qualitative or quantitative approaches, only a limited quantity of general data could be acquired. Work[8] can process data more quickly, obtain relevant assessment data in the shortest amount of time, and generate a more comprehensive calculation result by utilising Internet's high speed, rapidity, convenience. To create a more rigorous as well as analytical evaluation method, author [9] will examine and study traditional evaluation method to identify its flaws. Finding more sensible indicators and assigning them scientific weights via a range of calculations is the ultimate objective. Excellent higher education is stepping up to meet challenges of twenty-first century as China enters a new period of aggressively pushing socialist modernization. Word segmentation and part-of-speech tagging are two of the four major natural speech processing problems that Work [10] effectively resolved by utilising a word embedding technique in conjunction with a multilayer one-dimensional convolution structure. Author [11] proposed utilising a multilayer neural network to train high-dimensional features into low-dimensional characteristics to overcome issue of dimension disaster. Additionally, he proposed a layer-by-layer training technique to solve issue of deep learning training being difficult to do optimally. Work [12] built a recursive neural network to generate a sentence grammar analysis tree, employed DL technology to assess sentiment in sentence text, and fed the full phrase's grammatical structure as a feature to the model's training. In a similar vein, [13] identified the students who could fail based on environmental variables and the student data that was requested at registration. He discovered that employing DM techniques allowed for a more accurate classification of kids who might have difficulties. Additionally, their method enables the kids to be ranked according to risk levels. A machine learning-based approach was presented in work [14] to identify the main determinants influencing school academic achievement and to ascertain the relationships between these elements. The results of random forest method also showed that number of females enrolled in school and its size had a significant influence on model's predicted accuracy. In order to determine if pupils' academic performance was at jeopardy, author [15] put out a machine learning-based methodology. They predicted with an 85% classification accuracy by taking into account the students' learning styles, study habits, and academic interaction characteristics. The researchers came to the conclusion that students who struggle academically may be identified using the model they had developed. A machine learning model based on learning techniques, motivation, perceptions of social support, sociodemographics, health, and academic performance factors was proposed in work [16]. By gathering data from the campus Wi-Fi network, Reference [17] suggests an education assessment system to describe educational behaviour. The findings demonstrate that the system is able to gather data regarding the connection between academic achievement, distraction, and punctuality. Reference [18] simulates the student's answering process using an enhanced recurrent neural network based on student's answer records as well as exercise content in order to forecast student's success in the future. Reference [19] developed a prediction technique based on a neural network and clustering algorithm to mine learning rules during learning process using learner behaviour data from MOOCs. Every student can receive customised guidance based on the anticipated outcomes. Using input parameters including gender, income, board marks, and attendance, this machine learning technique, Naïve bayes, 1-NN, MLP forecasts students' performances. In order to enhance the model's performance, they used correlation-based feature selection (CBFS) strategies. They discovered that SMO outperforms other approaches in terms of effective average testing accuracy, achieving 66 percent.

4. Proposed mobile edge computing with lightweight security model for students database management:

Dispersed computing is required because tasks related to mobile edge computing typically entail dispersed messing. In the context of distributed computing, cloud computing controller typically distributes computing tasks to any networked computing resource that is available to finish them, returning them to computing requestor once unified processing is complete. Even while a single set of network equipment can currently handle more than THz of bandwidth, it is still insufficient to handle the enormous number of concurrent jobs. For instance, users sometimes have unusually slow Internet access, regardless of the type of connection that is available. (1) An excessive amount of concurrent computing task requests will overload the server even if the volume of data for each task is not very great; (2) the service request's communication link is too long and frequently requires passing through several routers in order to reach target server; (3) Naturally, router arrangement's operator is unable to handle the surge in requests for computing tasks if they do not adhere to the maximum demand to create.

A reliable Registration Centre (RC), mobile users, and MEC servers make up a MEC environment in most cases, as Fig. 1 illustrates. In this case, computational and storage functions are offered to MEC servers. These servers are installed in close proximity to the mobile users, usually at mobile base stations, and are geographically distributed. Their proximity to the users greatly improves the user experience by lowering latency. Mobile customers can use their cars, smartphones, tablets, and other devices to access MEC services. Conversely, the RC is regarded to be a reliable third party that assists in setting the cryptographic parameters and offers a shared registration platform for MEC servers and users. The suggested lightweight, privacy-preserving authentication mechanism requires the registration step. Cloud computing security issues are introduced when users outsource data to edge nodes with computing resources. This gives edge nodes control over the data. Because of the complex communication link, which increases the risk of data loss or malicious modification, it is difficult to guarantee confidentiality as well as integrity of data. Unauthorised entities may also use the uploaded data for their own benefit through privilege escalation. Edge servers have partially overcome the privacy and data security problems brought on by multihop routing's long-distance transmission when compared to cloud servers. But the access networks owned by many telecom operators and the apps that are mostly from different application suppliers have forced MEC to implement increasingly stringent data privacy regulations, like the coexistence of multiple security domains and data in varied forms.

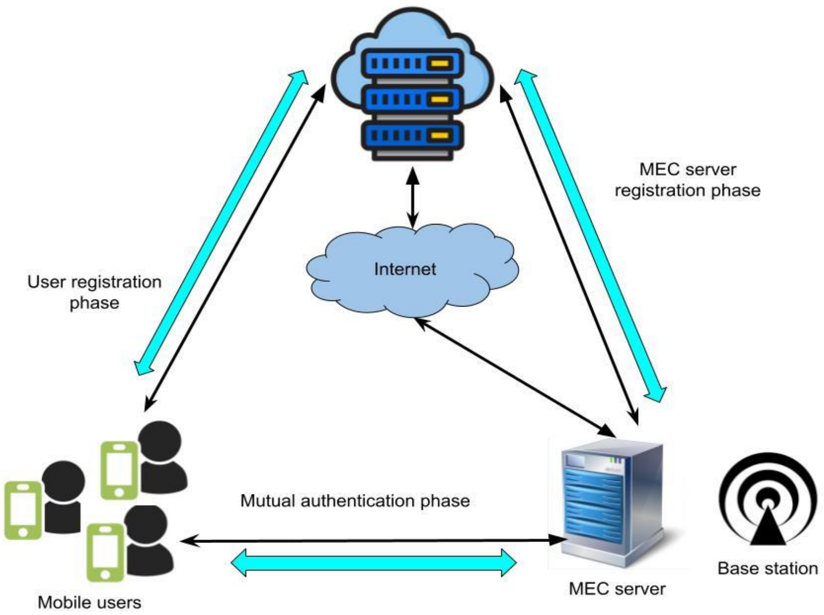

Figure-1 MEC based with lightweight security model in students database management

The MEC server receives the identity information from node X, and it then asks the authentication centre for upper layer protocol authentication. Subsequently, the MEC server receives an authentication response from the authentication centre. MEC server performs the uplink PHY-layer authentication when protocol authentication is verified. Finally, node X completes downlink physical layer authentication. PHY-layer access authentication procedure is finished in its entirety. Once access authentication has been implemented by the MEC server and node X, PHY-layer data authentication takes place. Subsequently, the MEC server will authenticate each incoming packet's PHY-layer data. It will be carried out to verify that data integrity has not been compromised by malicious alteration. In the event that the edge nodes lack computational resources, PHY-layer data authentication can be carried out in the MEC server.

5. Students interest in political education using reinforcement convolutional adversarial radial neural networks (RCARNN):

A recording of an environment interaction episode is made using the following information: the agent's beginning state (s), the action it took (a), the reward it received (r), and the agent's final state (s'). Set of states (S) and set of actions (A) are kept track of by our agent in a table Q[S, A]. One piece of data for value of Q[S, A] is an experience (s, a, r, s'). Equation (1) is used to update Q table with each data point.

$$Q_{t+1}(s,a) = Q_t(s,a) + \alpha[R(s,a) + \gamma \max Q_t(s',a) - Q_t(s,a)] \quad (1)$$

We examine a discrete time domain in which each time occurrence t denotes the RL algorithm step in which the QC makes a choice and switches between states, that is, assigns a particular query to a particular QP. The collection of potential actions (assignments to other QPs) A (st) and the state (assignment) st that the QC senses at t. It selects an action (a ∈ A (st)) and obtains a reward (rt ∈ R) and a new state (st+1) from the environment. Reward values r1, r2,..., rN are normalised in [0,1], it should be noticed. Furthermore, A qi, πj is concluded following qi's assignment to a certain family. These parameters might include, for example, the amount of time πj needs to run a query, the final QoR that the assignment A qi returns, πj, and so on. The following formula applies to MDPs without terminal states: With γ ∈ (0, 1] representing the future reward discount factor, R = ∑t γ t rt. In order to achieve a particular objective, the QC must choose the right Q.

Convolutional filters are sliding-window style linear functions applied to the input data. Let us represent a filter, for example, by θ = (µ1,..., ?w). Recall that θ represents a linear function that maps Rw to R. The i-th element of the output y that results from transforming x by filter θ, given an input vector x 2 Rn, is given by eqn (2)

$$y_i = f(\sum_{k=1}^{W} \theta_k x_{i+k}) \quad (2)$$

Zero-padding can be used to prevent this reduction. There are a tonne of web resources available to help learn about convolutional networks. Since the filter is applied uniformly over the feature space, input—such as photos or time series—must have some sort of meaningful topology. It has been demonstrated that convolutional networks are quite efficient at tasks like speech and picture recognition. This results in a collection of fresh feature maps, or refined renditions of the picture. Typically, filters in computer vision are trained to extract features that are helpful, like edges in various orientations. There is typically a non-linear transformation applied to the resultant pixels. Subsampling or pooling is another method that is frequently employed in computer vision. The reasoning behind this is that most of the most important information can still be seen in subsampled photos. The user has the option to select how many stacked convolutional and subsampling layers are used. The finished feature maps can then be compressed into a high-dimensional vector, which can then be supplied to a classifier—such as a fully-connected neural network—for further processing.

To enable a higher learning rate, batch normalisation using a gradient descent optimizer was also employed. To handle a dataset with mixed types of variables, loss of continuous and categorical variables with independent weights was combined. We utilized a greedy search approach to get the optimal set of hyper-parameters. This approach was taken because there were a lot of hyperparameters that needed to be adjusted during the GAIN training process. Generative adversarial networks are then used to further classify clustered data (GAN). This deep generative model is employed in both supervised and semi-supervised learning scenarios. The generator and discriminator modules are part of the network model. While the discriminator assesses the legitimacy of the samples, the generator model creates realistic data. Discriminator is taught to distinguish between actual as well as fake samples from dataset, generator is trained to supply discriminator with fake examples. The multilayer perceptron model for both generator and discriminator is the GAN model utilised in the suggested study. GAN can learn a variety of data and its internal representations better than conventional learning models. GAN can handle complex data efficiently and delves into data, allowing for easy interpretation of many versions. GAN is used in suggested health care data classification because of these further advantages.

To produce realistic samples, generator in the suggested method learns to map noise space into sample space. Probability classes for actual sample that was taken from dataspace are provided by discriminator module. The generator and discriminator functions are as follows in order to achieve minimax optimisation by eqn (3)

$$\min_{Gc} \max_{De} \mathcal{V}(\mathcal{D},\mathcal{G}) = \sum_{x\sim \text{ pdala } (x)} (\log\ D(x)) + \sum_{z\sim p_z(z)} (\log [1 - D(G(z))])$$

$$\varphi_1 = \frac{\sum_{i=1}^{M} x_1^{\{i\}}}{M} \tag{3}$$

where the samples are represented by M. All of the genuine and fictitious samples are taken into account while estimating the covariance matrix, which is stated as in eqn (4)

$$\Sigma = \frac{1}{N+M-2}\left[\sum_{i=1}^{M}\left(x_0^{\{i\}} - \varphi_0\right)\left(x_0^{\{i\}} - \varphi_0\right)^T + \sum_{i=1}^{M}\left(x_1^{\{i\}} - \varphi_1\right)\left(x_1^{\{i\}} - \varphi_1\right)^T\right] \tag{4}$$

where the bogus data is represented by u. The loss function is represented by the function found in Eq. (4). Based on the probability distributions of the produced and real data, the optimal discriminator output is obtained and is provided as in eqn (5)

$$\mathcal{D}^*(x) = \frac{p_{\text{data }}(x)}{p_{\text{data }}(x) + p_g(x)} \tag{5}$$

where the probability of created data is represented by p_"data " (x) and the probability distribution of genuine data is represented by p_"data " (x). Using both fictitious and real samples, the discriminator probability output is calculated and presented as eqn (6)

$$\mathcal{D}(x) = \frac{e^{\left[-\frac{1}{2}(x-\varphi_1)^T \Sigma^{-1}(x-\varphi_1)\right]}}{e^{\left[-\frac{1}{2}(x-\varphi_1)^T \Sigma^{-1}(x-\varphi_1)\right]} + e^{\left[-\frac{1}{2}(x-\varphi_0)^T \Sigma^{-1}(x-\varphi_0)\right]}} \tag{6}$$

Numerous academics have also applied particle swarm optimisation and genetic algorithms to design of radial basis function neural network structures; however, classification process may take longer to converge. As of now, no dependable algorithm exists to address this issue. Additionally, current RBF neural network model construction method fixes basis width of the Gaussian function, which introduces a slow convergence speed into the network during training. This study proposes a radial basis function neural network approach with a changeable basis width factor, which can significantly lower sample parameter needs and increase the classification accuracy of neural network models.

Three layers make up the radial basis function neural network model: (1) input layer, which is made up of input vector x = (x1, x2, · · ·, xn); (2) hidden layer, which has m neurons with a transfer function of hi; (3) output layer, which is made up of the RBF neural network's hidden layer's output information. RBF neural network's input and output are related in a way similar to a mapping connection, f (x): Rn → R. Network is connected to its surroundings and the input patterns are applied in the first layer. The network's only hidden layer, the second layer, uses the radial basis function. The network's responses are applied to the activation pattern in the output layer, which is linear. The multivariate input-output relationship is provided by eqn (7)

$$\boldsymbol{y}_{ij}(\mathbf{x}) = \sum_{j=1}^{K}\sum_{i=1}^{N}\mathbf{w}_{mj}\mathbf{G}(\|\mathbf{x}_i - \mathbf{c}_m\|) + \mathbf{b} + \mathbf{e}_{ij} \tag{7}$$

For this experiment, we used a normal multiple-input, single-output RBFNN. Of the 182 cases, 128 cases (or 70.3%) were assigned to the training sample, while 54 cases (or 29.7%) were assigned to the testing sample. The standardised rescaling approach was selected for the covariates. Softmax was used as the activation function and five units were used in the design of the hidden layer. Five units were used in the design of our RBF since testing data shows that this criterion produces the least amount of error. D5, the dependent variable, represents the output layer. In actual use, the questionnaire was built with five units or data points, and the "identity" activation function was used to collect responses on a Likert scale from 1 to 5.

6. Results and discussion:

We utilised Python to extract and display our results after this phase of data analysis, allowing us to see useful information as well as trends in student grade achievement across different courses. Data visualisation enables teachers to identify all the features and insightful information in the student dataset, helping them improve their students' academic performance so they may make better judgements in the future. We also compare each of the outputs of our proposed model using a more graphical approach to help understand the results even better.

Dataset description:

Data set utilized in this work was obtained from a learner activity tracker program's experience API (xAPI). It is simpler to monitor a learner's progress and their activities, including writing articles, watching videos, or reading articles, xAPI's learning and training architecture (TLA). Using xAPI, facilitator of learning platform can identify learner, activities, any other pertinent components that could help with addressing learning practice. Collection contains 480 student records and 16 attributes. These qualities are grouped into three main categories: (1) Demographic characteristics, like gender and nationality. (2) Features related to academics, like grade level, educational stage, section. (3) Behavior-related traits including raising a hand in class, using resources, polling peers, feeling happy at school. The dataset collection involves two professors. For instance, the European Expert Network on Economics of Education (EENEE) and Network of Experts on Social Aspects of Education and Training (NESET) are funded by European Commission in Europe. The Commission receives reports from these networks, which are subsequently used to inform official messages. The OECD publishes short notes called Pisa in Focus, which provide policy recommendations derived from data analyses of its PISA (PISA programme).

Table-1 Comparative based on various dataset

Dataset	Techniques	Training accuracy	Mean precision	Recall	Data integrity	THROUGHPUT
EENEE	GCNN	76	67	65	74	71
	SV-FFN	78	74	73	76	73
	RCARNN	83	79	77	80	75
NESET	GCNN	71	75	72	75	72
	SV-FFN	75	80	76	79	77
	RCARNN	85	87	80	81	86
PISA	GCNN	82	77	85	83	85

	SV-FFN	84	82	89	90	92
	RCARNN	95	93	94	97	98

The above table 1 shows comparative based on various dataset. Parametric analysis has been carried out for EENEE, NESET, PISA datasets in terms of training accuracy, mean precision, recall, F-1 score, RMSE and THROUGHPUT. The increasing trend of overall user satisfaction will be slowed down when there are more task owners than six. This is because there are currently less resources available to meet demand, which causes the quantity of resources allotted to each task owner to steadily decline. Conversely, it is clear that task owners' average revenue is trending downward. This is because there are now insufficient resources available, which drives up the cost of resources and lowers task owners' average revenue. When compared to the smaller μ, the weights in the interval [1.0, 6.0] indicate that task owners are not as demanding of resources. Even in situations where there are not enough resources available, task owners' overall satisfaction levels continue to rise upward. When there are a lot of task owners, the upward trend in the average returns will eventually level out due to the resources' progressive price increase. The following are the traits of each kind of student:

(1) Type 1 students drink more frequently but at lower monthly amounts, with a single-month high. This kind is included in the category of less consumed goods. These pupils come from low-income families and lead thrifty lifestyles. It is advised that school officials pay attention to living circumstances of these pupils, that when identifying and funding underprivileged students, they take these students into consideration when making selections.

(2) Type 2 students had the greatest average monthly consumption, highest number of consumption, highest consumption peak, suggesting that they are a high consumption group in the cafeteria.

(3) Type 3 students consume more than average each month, with a consistent monthly consumption amount and a greater monthly frequency of consumption. It demonstrates how frequently these students eat in school cafeteria and how consistent their consumption is, which is consistent with the typical eating habits of the majority of students in schools.

(4) Type 4 students have a moderate monthly consumption level, with a low average monthly consumption. On the other hand, both the monthly maximum consumption and the total number of consumptions are quite minimal. These pupils typically choose to buy takeaway or dine outside of school, and they eat irregularly in cafeteria.

(5) For type 5 pupils, the maximum intake is not great, number of times is not large, average monthly consumption is modest. These pupils are more likely to eat and drink outside of school and are less likely to attend the cafeteria. School authorities ought to be concerned about these youngsters' personal safety as well as the safety of their food.

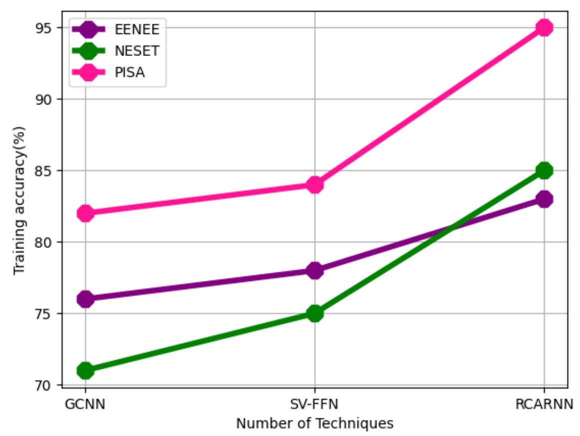

Figure-2 Comparative analysis of training accuracy for EENEE, NESET, PISA dataset

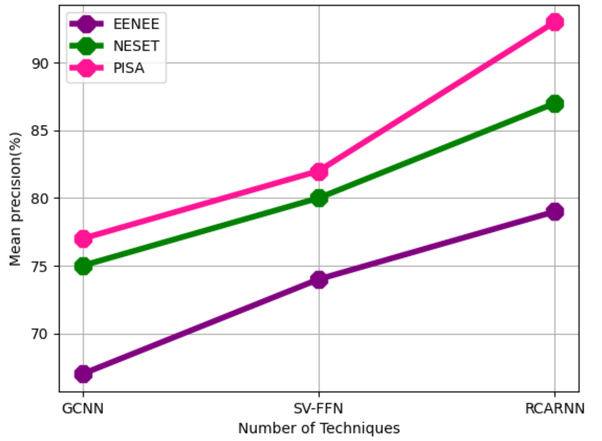

Figure-3 Comparative analysis of Mean precision for EENEE, NESET, PISA dataset

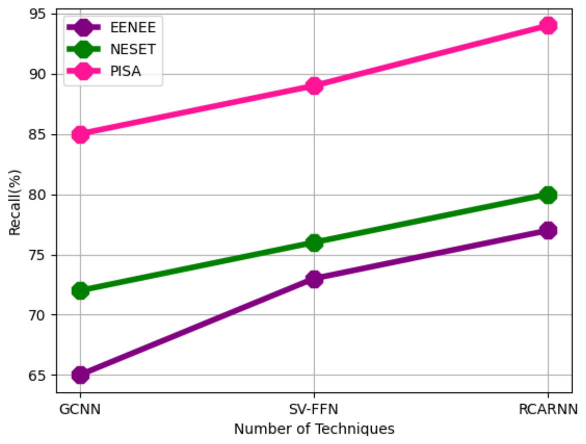

Figure-4 Comparative analysis of recall for EENEE, NESET, PISA dataset

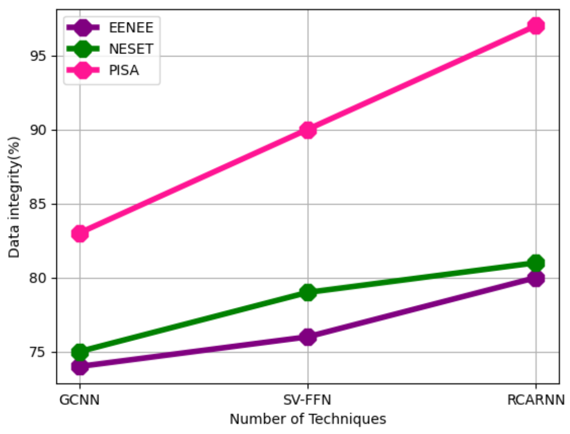

Figure-5 Comparative analysis of Data integrity for EENEE, NESET, PISA dataset

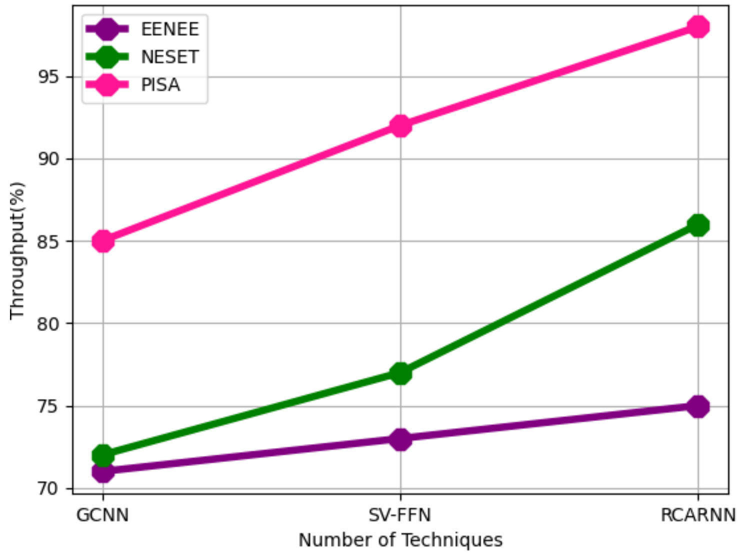

Figure-6 Comparative analysis of Throughput for EENEE, NESET, PISA dataset

Figure 2-6 shows comparative analysis based on various dataset. In this case, suggested method achieved training accuracy of 83%, mean precision 79%, recall 77%, data integrity 80%, Throughput 75%; current method, GCNN, achieved training accuracy of 76%, mean precision of 67%, recall of 65%, data integrity of 74%, and Throughput of 71%; for the EENEE dataset, SV-FFN achieved training accuracy of 78%, mean precision of 74%, recall of 73%, data integrity of 76%, and Throughput of 73%. The suggested technique for NESET dataset achieved training accuracy 85%, mean precision 87%, recall 80%, data integrity 81%, Throughput 86%; existing GCNN technique achieved training accuracy 71%, mean precision 75%, recall 72%, data integrity 75%, Throughput 72%; With training accuracy 75%, mean precision 80%, recall 76%, data integrity 79%, throughput 77%, SV-FFN achieved these results. The suggested method achieved 95% training accuracy, 93% mean precision, 94% recall, 97% data integrity, 98% Throughput; current method, GCNN, achieved 82% training accuracy, 77% mean precision, 85% recall, 83% data integrity, 85% Throughput; for PISA dataset, SV-FFN achieved 84% training accuracy, 82% mean precision, 89% recall, 90% data integrity, 92% Throughput. With the use of data mining and ML approaches, assessment tools have recently been developed in the education industry to predict student achievement. Evaluation of student performance is a crucial educational measurement metric that influences institution accreditation. In those universities, a plan for improving student performance must be put into action by advising underachievers. It assists teachers and students in resolving issues that arise from the student's studies and the methods of instruction used by the teachers.

7. Conclusion:

In order to manage student databases and analyse student interests for political education's ideological component, this research proposes a unique technique in mobile edge computing intelligence with a lightweight security model. In this case, the management of students' educational interests and their idealogy for political education is done through the use of reinforcement convolutional adversarial radial neural networks, together with mobile edge computing with lightweight security models. This model can gather detailed information from several smartphone sensor signals, which raises methods overall classification accuracy. Through experiments, proposed method classification performance is compared as well as assessed. When suggested method was put up against conventional behaviour recognition techniques, it did better. Each evaluation index has a unique weighting as a result of rigorous data training, and the evaluation result value is computed automatically using the evaluation data. The algorithm's efficiency is increased and processing times are shortened by continuously adjusting the model parameters in response to freshly provided sample data. We verified that the incremental learning approach can improve the evaluation model and time efficiency when the evaluation data is larger by conducting experiments and analysing the results.

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